Universität Basel

Wirtschaftswissenschaftliche Fakultät

WWZ

Preference Revelation and Choice Modelling of Transportation Modes. Evidence from a Stated Preference Experiment.

Master Thesis

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Submission Date	**26.06.2020**

Abstract

This work analyses transportation mode choice behaviour in urban agglomerations in Switzerland. Based on data from a stated preference experiment and using mixed multinomial logit models, it has the form of an exploratory study that collects first insights.

Results show on the one hand that the inclusion and manipulation of external costs had only reduced effect on choice behaviour. The majority of the participants did not consider the relatively less expensive public transport or bike alternatives. Preferences for a transportation mode seem solidified. Apart from travel time, they can more readily be explained by transport means equipment and sentiment on issues of transportation like congestion or CO_2 emission. Alternative departure times by car were considered more easily.

On the other hand, this work also notes on the challenges in the process of deriving robust random parameter models and the broad range of possible settings. The estimated values of travel time savings (VTTS) as well as a high number of iterations until convergence call for additional robustness checks and the testing of alternative model specifications.

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1. Introduction

1.1. Context and motivation

Human decision-making processes are inherently complex. Influenced by countless factors and often driven by intuition, we make thousands of decisions every day. Some are less, others more important on our lives, some are of short-lived nature, others are long-term decisions. Our choices, however, reveal information about our subjective preferences which allows for subtle influence and nudging. When it comes to designing smart policies in order to react to some of the great challenges our societies face today – climate change being an obvious example – it is of great importance to understand from a micro-level how individuals make their decisions. These can be decisions like which products we buy, which meal we choose at lunch in the cafeteria or the choice of our preferred means of transportation to get to our work or study place.

In an aggregate perspective, such decisions can have huge implications. For a developed country like Switzerland, the choice of transportation mode is of special importance from a societal and ecological perspective. From the year 2000 to 2018, passenger traffic in Switzerland increased by 33% to about 136 billion kilometres in 2018 (BFS 2020). In the year 2015, this meant that the average citizen travelled 37 kilometres each day within Switzerland (BFS 2017). This degree of mobility comes at a high price. For the year 2016, the costs for accidents have been estimated at about 7.5 billion CHF and environmental and health related costs at about 9 billion CHF (including aviation) (BFS 2019). These costs are to a large extent not borne by the producer but are externalized to society, as the BFS (2019) writes. Additional economic costs, for example from the time people (and goods) spend in traffic jams, must be considered as well. Furthermore, in order for Switzerland to be in line with the international binding goals of the Paris climate change agreement, the reduction of CO2 output coming from individual traffic will play a considerably role.

These are all facets of a problem which is in part caused by individual choices of how to cover daily trips and which makes congruent mobility policies potentially highly fruitful in a number of areas. For policy makers it is therefore of great importance to understand how individuals decide on their transportation mode and which factors drive their decision: Are people willing to pay more in order to switch to a transportation mode which produces fewer external costs? How do they price their travel time and potential time savings? Which factors influence the decision for a certain transportation mode the most? And is it possible to make people more sensitive to the negative consequences they produce with their travel behaviour? These are some of the relevant questions this thesis circles around and where the analysis of data from choice behaviour helps to find answers. In economics, such questions are classically processed and statistically evaluated using random utility models that allow to quantify subjective preferences. Instead of modelling aggregate level data, discrete choice models demand data at a disaggregated level, where every data point represents a performed choice by an individual. Funded by Swiss Federal authorities, the MOBIS Research Project (2019) collected a comprehensive dataset on mobility behaviour in Switzerland. Part of this dataset is a stated preference (SP) experiment which collected participants choices for different transportation modes and will serve as the starting point of this work.

1.2. Research objectives and delimitations

This thesis has the form of an exploratory study on the decision making between transportation modes in urban settings. It is based on the data of the SP experiment collected within the MOBIS Research Project (2019). The statistical analysis of the data is mainly done using mixed multinomial logit (MMNL) models which allow for random taste heterogeneity and are considered as state-of-the-art for discrete choice modelling.

On a content level, we explore different factors that are thought to drive individuals' decision-making in this context. More specifically, we investigate how people value their travel time under different transportation modes. Additionally, the role of external costs on decision-making is examined. To the best of our knowledge, there is a lack of studies that consider external costs in transportation mode choices for Switzerland. In an ideal case, some critical factors and implications for transportation policies can be highlighted. On a theoretical-methodological level, the work collects findings on the feasibility of a mixed logit approach to the MOBIS data, and notes on the procedure for creating mixed logit models. As an investigatory work, it builds up knowledge and collects best practices for further research on the MOBIS data set. The study is limited in the sense that no new data is collected as it fully builds on the already conducted experiment and its resulting data which focuses on urban agglomerations in Switzerland.

1.3. Structure of the thesis

The thesis comprises five chapters. Chapter 2 describes the theoretical and methodological foundations this study is based on. Section 2.1 and 2.2 provide a short introduction to choice-modelling and mixed multinomial logit models whereas Section 2.3 investigates related literature and best practices our analysis can profit from. Section 3.1 explains the stated preference experiment that was conducted in the MOBIS project and 3.2 summarizes the data that is used in this thesis. Chapter 4 contains the empirical parts of this study. Section 4.1 gives an insight into the procedure that was followed, and Section 4.2 explains settings to be considered in mixed MNL models. In Section 4.3 some descriptive evaluations of the data were done, including an analysis of trading behaviour and a descriptive analysis of participants response times. Section 4.4 discusses the model outputs; Section 4.5 mentions the issue of correlation and Section 4.6 provides calculations of value-of-travel-time-savings (VTTS). Chapter 5 highlights the most important findings, as well as the study's limitations and ends in a discussion of further improvements of the model and possible future research.

2. Theoretical and Methodological Foundations

2.1. Modelling discrete choices

Disaggregated models of individual behaviour try to model and to predict human decision-making in (discrete) choice situations. The framework for discrete choice models includes four basic ingredients (Ben-Akiva and Bierlaire 1999): (1) a decision-making entity with its characteristics, (2) a (mutually exclusive, finite) set of available options, (3) the attributes to the alternatives (which can be alternative-specific or generic to each alternatives) and (4) a decision rule followed by the decision-maker. For the latter, economists make use of the concept of utility. In simple terms, utility theory is based on the belief that a consumer derives a benefit from consuming a product or service by satisfying a need. According to the theory, this benefit, called utility, is what the consumer tries to maximize in any situation. For discrete choices, the preference of the consumer for an alternative depends on his or her own (cardinal) utility attached to this alternative. The consumer's utility is not known to any observer but when choosing between alternatives, the decision-maker discloses their preferences and makes it possible to infer to his or her utility function (Hensher et al. 2015).

Of course, it is well known that human decisions are not completely deterministic, and we need to account for a probabilistic part. Random utility theory adds uncertainty to the deterministic decision rule of utility maximizing behaviour. It can be interpreted as either incomplete information on part of the researcher or as the intrinsically probabilistic nature of human decision-making. In order to model the behaviour, a random distribution with some density must be assumed. Following Train (2009), a random utility model (RUM) is derived by defining a utility U_{nj} of decision-maker n for alternative j. As mentioned before, this utility is not known by the external observer, who can only observe some attributes of the decision-maker and the alternatives of the choice situation, which are summarized by V_{nj}. Factors that are unobservable are named ε_{nj}, so that the general utility for alternative j consists of $U_{nj} = V_{nj} + \varepsilon_{nj}$. The unobserved factors are treated as random with density $f(\varepsilon_n)$ for the random vector $\varepsilon_n = (\varepsilon_{n1}, \ldots, \varepsilon_{nJ})$ over all alternatives J. Modelling choices means modelling the probability of a particular outcome. With the density $f(\varepsilon_n)$, the cumulative probability is an integral

$$P_{ni} = \int_{\varepsilon} I(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \; \forall j \neq i) f(\varepsilon_n) \, d\varepsilon_n \tag{2.1}$$

in which the indicator function $I(.)$ is equal to 1 if the random term $\varepsilon_{nj} - \varepsilon_{ni}$ is smaller than the observed part $V_{ni} - V_{nj}$ (and 0 otherwise). Depending on the chosen distribution of the random part, the choice probabilities can either be calculated from a closed form formula or must be approximated by simulation. While the latter one is applicable to almost any model specification, a closed form expression only works for some specifications of $f(\varepsilon_n)$ (Train 2009).

For a long time, multinomial logit (MNL) models have been the standard for discrete choice modelling. With their closed form expression, they are easily computable. But the computability comes at the cost of the strict assumption that the unobserved part of the individual's decision-making is independently and identically distributed extreme value (Train 2009). In practice, the assumption on independence means that the unobserved portion of utility of one alternative is in no way related to the unobserved portion of utility for any other alternative. But as one can imagine, the error terms between alternatives often are correlated. Of course, as Train (2009) states, the best way is to specify a model such that the question of correlation can be minimized, but in many applications, this seems unrealistic. Additional issues arise if one expects differences in tastes of the decision-makers that cannot be related to observed characteristics. Or if there are substitution patterns of alternatives that are not proportional to each other, meaning that the introduction or change of an alternative, changes the ratio of probabilities for the existing alternatives (see for example Train 2009, pp. 45-49). In choice theory this phenomenon relates to the Independence from Irrelevant Alternatives (IIA) property and is one of the shortcomings of the standard logit model.

Mixed models can overcome these issues, in that the random term is decomposed so that one part can be solved analytically, whereas the rest is being simulated. These models bring together the advantage of analytical integrals, which are more accurate and easier to calculate, and the easing of the constraints of pure closed form models. Mixed multinomial logit (MMNL) models are one example of such an application.

2.2. Mixed multinomial logit models

The three limitations of standard logit models, the independence assumption of unobserved factors over time, the constraint on random taste variation and the restricted substitution patterns, can be bypassed using random parameter models like MMNL. The mixed MNL model assumes that the beta coefficients vary over the population. Each subject gets their own beta and the coefficients show an estimated mean and standard deviation from a predefined population distribution. The result is a highly flexible model which allows one to approximate any random utility model as closely as one likes to (McFadden and Train, 2000). Of course, it is possible to keep some elements of the model fixed and make it standard logit again. The mixed logit probability

$$P_{ni} = \int \left(\frac{e^{\beta' x_{ni}}}{\sum_j e^{\beta' x_{ni}}} \right) f(\beta) d\beta \tag{2.2}$$

differs from the logit formula only in that it has a density function $f(\beta)$, which creates a weighted average from the different values of β (Train 2009). The mean and covariance of $f(\beta)$ are then estimated using maximum likelihood estimation. All possible distributions can be chosen while utility maximizing is guaranteed by the approximation process. This results in a highly flexible model which, depending on the purpose of the analysis, can take many different specifications. More details about the specification of mixed MNL models is provided in Section 4.2 where it is applied to our data.

Viton (2004) argued that the mixed logit model will completely replace standard logit models for the study of discrete choices. He asked how this could potentially change some of the policy conclusions from older models and investigated it by comparing a set of policy conclusions regarding private bus transit provisions in urban settings to a mixed logit model specification. Although conclusions and policy recommendations do not change completely, he was able to gain additional insights regarding some policies that were not available in the standard logit case. We can expect for our study as well to gain more insights when we make the effort of following a mixed logit approach.

2.3. Related literature on transportation choices

Some of the earliest applications of logit models were in the context of transportation and mobility. In the mid-1970s, Daniel McFadden and others (McFadden et al. 1977 in McFadden 2000) estimated future demand for a new rail system in the San Francisco Bay area. Their choice models were able to predict future demand much better than the initial estimations by project authorities. Since then many applications of logit, and today mixed logit, models to transportation choices have been made. However, it is in the nature of disaggregated level data that the decisions belong to a specific context with a specific set of alternatives. Even though it is possible to work with pooled data that was collected over several decision contexts and then use the decision context as an explanatory variable, inference-making is more difficult than for aggregate level data (Hensher et al. 2015, p. 31). Nevertheless, this section mentions some applications from which our analysis can profit.

In the economics discipline among others, a lot of focus is put on willingness to pay (WTP) indicators, such as values of travel-time savings (VTTS). In a paper by Axhausen et al. (2008), a stated preference study, like the MOBIS study based on observed trips, investigated mode and route choices depending on the trip purpose (business, commuting, leisure or shopping). The analysis of the VTTS estimates for commuting trips, which are the most relevant for our study, results in 28 CHF/h for public transport (PT) and 31 CHF/h for car, while taking account of income and trip distance and showing an income effect for PT commuters as well as car commuters. A more recent Swiss study (Schmid et al. 2016) found VTTS around 20 CHF/h for PT in-vehicle time and around 60 CHF/h for travel time spent on a bike. As their study aimed at gaining insights into how possible future restriction on individual car ownership could influence choices for transportation modes, they investigated car-sharing and car-pooling modes, where the former showed VTTS of low 11 CHF/h and the latter VTTS of around 25 CHF/h. In comparison, Schmid et al. (2019) used Austrian data to examine mode and user-type effects in VTTS. While the income level differs from Austria to Switzerland, the relative differences between transportation modes are interesting: the authors found VTTS estimates of 12 Euro/h for car, 8 Euro/h for public transport and again about 12 Euro/h for bike rides. They further wrote that "characteristics of the mode are more important than characteristics of the users and that the travel time spent in PT is valued less than in a car for all investigated user groups" (Schmid et al. 2019, p. 262).

Hess et al. (2005) also investigated implied VTTS calculated from discrete choice models with random taste heterogeneity. Their work is special because they explicitly investigated cases with non-zero probability of positive travel-time coefficients, which on the first view contradicts any theory of rational economic behaviour but nevertheless can arise quite frequently. In general, such problems are avoided by using distributions bounded at zero, but as Hess et al. (2005) showed, unobserved attributes on travel-experience (for example a not measured comfort factor) or conjoint activities (such as for example working while commuting) can bias estimations and call for different interpretations. They suggested to nevertheless use bounded distributions but to estimate the bounds first to reduce the risk of bias coming from the shape of the chosen distribution. Going in a similar direction, Bastin et al. (2010) presented different specifications to a mixed logit model and applied it to stated preference data from a survey on mobility behaviour in Brussels. Much like our data from the MOBIS Research Project (2019), Bastin et al. (2010) followed car users that commute during daily peak hours and presented them with alternative transport modes, among them delayed departure times and public transportation. Having a somewhat smaller dataset than ours and only taking 7 random parameters out of a total of 18 exogenous variables, they tried out different distributions for their time and cost coefficients and found that using a basis spline function improved their results compared to normal distributions. It is conspicuous however how much variability in VTTS exists between their different models and the difference of VTTS between free-float driving and congestion is very small compared to other studies. However, it shows again how sensitive mixed MNL models can react to distributional assumptions.

Instead of calculating marginal willingness to pay in a post-estimation process, it is also possible to estimate the whole model in a willingness to pay space (see for example Hensher et al. 2015). Scarpa et al. (2008) compared the two approaches, preference space versus willingness to pay space, using data on site choice in the Alps. Their starting point was the issue of counter-intuitive distributions of marginal willingness to pay. As they mention, this issue arises regularly when using normal or log-normal distributions for taste coefficients as the cost coefficients, which enter the denominator, are often close to zero and thereby create large ratios. As assuming the cost coefficients to be fixed instead of random is not plausible in many applications, parameterizing the model in a WTP space is often the better solution. In their application, the model estimated in WTP space outperformed the preference space specification. Scarpa et al. (2008) stated two other studies which compared the specification in the preference space to the WTP space (Train and Sonnier, 2005, and Sonnier et al., 2007, cited in Scarpa et al., 2008). In both these studies preference space specifications fitted in-sample data better. Not so for Scarpa et al. (2008) investigations though, where the model in WTP space outperformed. Also, the WTP space specification produced thinner tails of WTP distributions in all three studies.

Based on a broad study about factors influencing the demand for public transportation, Paulley et al. (2006) investigated the four most significant attributes, fares, quality of service, car ownership and income. As for the quality of service, attributes were obtained by stated preference experiments and include access and egress time. These are shown to weigh between 1.4 to 2.0 units of in-vehicle time for walking and quite similar for other access/egress modes like driving or cycling. Elasticities for attributes like frequency are calculated using the number of vehicle kilometres operated as indicator and shows to be positive with a short-run elasticity (1-2 years) of 0.38 and a long-run elasticity (12-15 years) of 0.66. Elasticities of in-vehicle time are not stated by Paulley et al. (2006) as their bus journeys are relatively short. However, they state several studies finding values between -0.4 to -0.9 for urban range journeys.

A vast number of additional studies concerning transport mode choices exists. The studies mentioned in this section give answers to a broad range of questions and show several important factors in modelling discrete choices. However, little has been done yet regarding the effect of external costs. To the best of our knowledge, this thesis is the first to attempt an investigation into transport mode choice behaviour in Switzerland which include the effect of external costs.

3. Experiment and Data

3.1. Experimental design

The data used in this thesis was collected within the research project «Mobility behaviour in Switzerland» (MOBIS). Funded by the Swiss Agency for Innovation Promotion (Innosuisse) and the Federal Department for the Environment, Transport, Energy and Communications (DETEC), the project aims “to gain new insight into how best to improve transport systems in urban agglomerations in Switzerland” (MOBIS 2019). Over 95'000 randomly selected citizens of major agglomerations from the German and French speaking part of Switzerland were invited to participate in an online survey on their mobility behaviour and their convictions on different transport policy measures. About 22’000 people finished the first online survey, out of which 5’693 were accepted to participate in a continuative smartphone tracking field experiment. Only people out of the working population, defined as age group between 18 and 65 years old were accepted. A further condition was, that they travel by car at least twice a week. Professional drivers were excluded. For the following two months, an app installed on their smartphones would automatically register every journey and the used means of transportation. Participants were asked to daily check the summary of their mobility behaviour. Weekly e-mails were sent to each participant which summarized their behaviour. The content of the e-mail depended on which of three groups participants were assigned to: a control group, a nudging group, and a pricing group. In the second month of the tracking experiment, the latter received real money values if they reduced the external costs of their journey, for example by taking the bike instead of the car. The nudging group received information about external costs their journeys would produce, but without receiving monetary benefits. The control group’s e-mail would not include any of that and just give some summarized information about their travel behaviour.

After the two-month tracking phase, a final online survey was conducted, as part of which respondents were asked to fill in a stated preference experiment. Each respondent was confronted with twelve binary choice situations that were built on the respondents’ most frequent car trip during the two months of tracking. As alternative option to using the car for this trip, either public transportation (PT), a bicycle (Bike) or a different (earlier/later) departure time by car (Alt) was proposed. Figure 1 shows an excerpt of the stated preference experiment, one with public transport, the other with an earlier departure time as alternative. An example with bike as alternative is shown in Annex 1. Beside the travel time and reliability of the transportation mode, each choice option also includes private costs as well as external costs, broken down in three sub-categories. Respondents were asked to state their preferred option for regularly recurring journeys and to consider the total costs compared to only the private costs they normally have to pay.

The public transportation option includes the most additional information like the number of changes, occupancy, frequency of the connection and hypothetical weather conditions. The bike option states additional health benefits, road conditions (for example whether there is a bike lane) and weather conditions. Also, it is stated whether an e-bike or a regular bike is used.

Figure 1: Choice situation examples of the stated preference experiment

	Option 1: Auto	Option 2: Auto
Abfahrt	16:03	17:03
Ankunft	16:16	17:22
Dauer	13 min	19 min
Verschiebung der Abfahrtszeit	-60 min	
→ Verspätung >10 min	Nie	alle 20 Fahrten
Gesamtpreis	8,25 CHF	8,95 CHF
privater Anteil	7,10 CHF	7,10 CHF
externer Anteil	1,15 CHF	1,85 CHF
→ Verursachter Stau	0,20 CHF	0,90 CHF
→ Gesundheits-/Unfallkosten	0,70 CHF	0,70 CHF
→ Klimaschäden	0,25 CHF	0,25 CHF

Option 1 ○ Option 2 ○

	Option 1: Öffentlicher Verkehr	Option 2: Auto
Abfahrt	16:18	17:03
Ankunft	17:11	17:22
Dauer	53 min	19 min
→ Fahrtdauer	45 min	
→ Zu- und Abgangszeit	8 min	
Hauptverkehrsmittel	Bahn	
Umsteigen	4	
Auslastung	hoch	
Takt	alle 20 min	
Verspätung >10 min	alle 20 Fahrten	Nie
Wetter	kalt, nass	
Gesamtpreis	3,70 CHF	8,00 CHF
privater Anteil	3,35 CHF	7,10 CHF
externer Anteil	0,35 CHF	0,90 CHF
→ Verursachter Stau	0,00 CHF	0,45 CHF
→ Gesundheits-/Unfallkosten	0,30 CHF	0,35 CHF
→ Klimaschäden	0,05 CHF	0,10 CHF

Option 1 ○ Option 2 ○

Source: MOBIS Research Project (2019)

The dataset containing the stated preference experiment data is exceptional in two ways. First because of its size and amount of information. A representative sample of 3387 persons filled out the stated preference experiment. For all of them, socio-economic information as well as information regarding their attitudes towards transportation policies and general issues in transportation are available. The second reason, which makes this dataset valuable is that choice situations are related to a trip the respondent has conducted in real life. This means that he or she can relate to the situation and the given information. Also, and very importantly, the choice situation captures an emotional relation to this trip, which makes the experiment more realistic. As an additional feature of the dataset, the time it took the respondents to make their decision was measured.

3.2. Data structure

The data from the stated preference experiment comes in form of a panel data set and was combined with data from the other online surveys. For the analysis, a total of 30’460 choice situations from more than 2’500 respondents were used. The main variables are the alternative specific pieces of information that were listed with each choice situation as seen in Figure 1. Table 1 gives an intuition for the three most important numeric variables private costs, external costs, and trip duration for all four choice alternatives.

Table 1: Summary statistics of cost and duration variables

Statistic	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
car_priv_cost	30,460	8.8	7.1	4.2	6.8	10.9
car_ext_cost	30,460	8.6	11.9	1.8	4.3	10.8
car_dur_mins	30,460	22.4	13.5	13	19	29
pt_priv_cost	8,148	2.8	2.9	1.5	2.1	2.8
pt_ext_cost	8,148	2.0	2.6	0.4	1.0	2.6
pt_dur_mins	8,148	46.7	22.5	33	42	54
bike_priv_cost	9,024	0.7	1.1	0.0	0.0	1.3
bike_ext_cost	9,024	2.0	2.1	0.5	1.1	2.6
bike_dur_mins	9,024	32.7	16.7	19	30	43
alt_priv_cost	13,288	10.0	8.2	4.4	7.3	13.3
alt_ext_cost	13,288	7.1	10.3	1.4	3.5	8.8
alt_dur_mins	13,288	16.9	11.4	9	14	22

The cost coefficients in Table 1 are in CHF. The private costs of a car trip show a median[1] of 6.80 CHF (or 7.30 CHF for the alternative option) compared to 2.10 CHF for a public transport trip or close to 0 CHF for a bike trip. Although calculated, the private costs should be close to the real costs respondents need to pay for their journey. The external costs were multiplied by 0.5, 1, 2, 4 or 8 with the purpose to create more variation and to test for any reaction. The high average value of 8.60 CHF of external costs as well as the large standard deviations are a result of that. The actual average external costs are in fact only 2.75 CHF. The median car trip has a duration of 19 minutes whereas public transport takes more than twice as long (42 minutes). The median bike journey takes 30 minutes. The numbers underline again that we are dealing with trips within agglomerations. Interesting to observe is that the alternative option is on average more than 5 minutes faster, as congestion could be bypassed with an earlier or later departure time. Regarding the number of observations, we see again that all choice situations had car as their baseline option.

Table 2 lists additional alternative specific variables. The reliability variable for Car, PT and Alt states how often the connection is more than 10 minutes late. Pt_mode includes four different modes, namely bus (47,0%), train (36,7%), tram (13,9%) and subway (2,4%). Car/PT decisions which contained walking as the main mode were excluded, as there are no costs

[1] In all instances, the Mean is higher than the Median, and the Standard Deviation is considerable, indicating a skewed distribution of the data. Since the Median is less affected by extreme values than the Mean, mostly Median values are discussed.

attached to this mode and the sample was relatively small. The variable pt_changes states the number of transfers to another public transport that are necessary on this trip and is treated as a numeric variable. Finally, alt_time_dep_shift states by how many minutes the departure time has been changed.

Table 2: Levels of categorical variables

Variable	Levels
car_reliability	1 - every 5 trips, 2 - every 10 trips, 3 - every 20 trips, 4 - never
pt_reliability	1 - every 5 trips, 2 - every 10 trips, 3 - every 20 trips, 4 - never
pt_mode	1 - bus, 2 - train, 3 - tram, 4 - subway
pt_frequency	1 - every 30min, 2 - every 20min, 3 - every 10min
pt_occupancy	1 - high, 2 - medium, 3 - low
pt_weather	1 - cold dry, 2 - cold wet, 3 - warm wet, 4 - warm dry
pt_changes	1 to 6 (integer)
bike_mode	1 - bike, 2 - e-bike
bike_weather	1 - cold dry, 2 - cold wet, 3 - warm wet, 4 - warm dry
bike_benefit	1 - low, 2 - medium, 3 - high
bike_bike_lane	1 - main road no lane, 2 - main road w. lane, 3 - residential or bike path
alt_reliability	1 - every 5 trips, 2 - every 10 trips, 3 - every 20 trips, 4 - never
alt_time_dep_shift	1 - -60min, 2 - -30min, 3 - +30min, 4 - +60min

Table 3 lists additional socio-economic and other variables that were added as controls. The age dummy is split at the median age of 42, which showed better results than entering it as numeric variable.

Table 3: Additional controls

Variable	Coding
female	1 - yes, 0 - no
age	1 - over 42 years , 0 - under or equal to 42 years
higher_edu	1 - tertiary degree, 0 - no tertiary degree
income	1 - 3'000, 2 - 6'000, 3 - 10'000, 4 - 14'000, 5 - 18'000
household_size	1 to 5 (integer)
own_car_dummy	1 - yes, 0 - no
has_pt_pass_halffare	1 - yes, 0 - no
has_pt_pass_regional	1 - yes, 0 - no
has_pt_pass_ga	1 - yes, 0 - no
congestion	1 - strong agree/agree, 0 - neither dis- nor agree/disagree/strong disagree
emission	1 - strong agree/agree, 0 - neither dis- nor agree/disagree/strong disagree
health	1 - strong agree/agree, 0 - neither dis- nor agree/disagree/strong disagree
statement_ext_costs	1 - strong agree/agree, 0 - neither dis- nor agree/disagree/strong disagree
factor_half	1 - yes, 0 - no
factor_double	1 - yes, 0 - no
factor_quad	1 - yes, 0 - no
factor_oct	1 - yes, 0 - no

The four variables in the third section belong to questions of the final survey in which participants were confronted with several potential problems associated with transportation. They were asked to rate on a scale of five “whether it should receive more or less attention from policy makers, compared to how much attention it currently receives” (MOBIS Research

Project 2019). Among others, problems stated were “road congestion”, “greenhouse gas emissions from motorized traffic” and “health effects of air pollution from motorized traffic”. These are represented in the dummies congestion, emission and health. The fourth dummy of this section is the rating to the statement “the price for mobility should reflect the social cost (e.g., health, environment, congestion)”.

4. Model Formulation, Data Analysis and Results

For this thesis, a mixed multinomial logit model approach has been followed. This chapter presents the analyses that have been conducted and the main results obtained. First, a brief introduction to the procedure that was followed is given. Then we look at the settings a researcher must choose when specifying mixed MNL models. The third section first discusses the results of the basic model and then turns to the extensions that have been made, which all aimed at making the models even more meaningful.

4.1. Iterative process of model formulation

Specifying mixed logit models can be a laborious undertaking. It is an iterative process of trial and error and not many hard facts exist about how a mixed logit model must be specified. For this work, dozens of model specifications were tried out. We used the R statistical software for the analysis (R Core Team 2015). During the estimation process two different packages were applied and evaluated. The “mixl” package is a recently developed package by Molloy et al. (2019) which has put focus on improving memory usage and runtime and is successful in doing so to a great extent. On the downside, not much experience exists yet and finding online instruction proved to be difficult sometimes. A second package, “mlogit”, was utilized as well but abandoned later. “Mlogit” is the most common R package for mixed logit models. It brings therefore the advantage of having some documentation online, but the estimation process is increasingly slow the larger the models get. Also, and this was problematic for our purpose, the “mlogit” package needs the dataset in long format. In our case, many choice attributes are alternative specific but only available for one option, such as “occupancy” for public transport options. For these reasons we turned back to “mixl” for the in-depth analysis.

In a very first step, simple logit models were investigated. The calculation time of standard logit models is insignificant, and it can help to gain first impressions about the data and model specifications. The first mixed logit models then focused on the main numeric attributes of the experiment, such as travel cost and travel duration. These models already showed two interesting things which held also in more comprehensive models later. First, in any specification travel as well as access/egress time parameters were highly significant. Private costs by contrast changed in its significance much more over different specifications and transportation modes and were significant only in some specifications. Yet these simple models were already able to produce a good overall fit to the data with a pseudo R^2 of up to 0.3. The second interesting observation concerns the external cost variable. Whether for models estimated with the mixl or the mlogit package, this variable often showed insignificant results. Splitting up the external costs, we could see that the costs from congestion most likely showed to be significant whereas costs from CO2 pollution and health related costs where highly insignificant in most models.

4.2. Settings for mixed MNL models

Before turning to the analysis of model outputs, it is important to look at the different settings one must choose for mixed MNL models. Unlike for example probit models, mixed logit models are not restricted to the normal distribution and any distribution one likes can be chosen. If a discrete function with a finite set of values is chosen, the mixed logit model becomes a latent class model. With one “mlogit” exception, up to now only normal distributions were used in our models, which allow the coefficients to take positive and negative values. But for example, cost coefficients, when multiplied with (-1), can receive a distribution bounded at zero, like log-normal distributions, which then prevents coefficients from turning positive (Train 2009). Unfortunately, such specifications could not be tested for our data yet.

For any model using maximum simulated likelihood, four factors define the parameter estimates (beside the data of course) (Gu et al. 2013): the random-number seed, the number of draws, the starting values and the optimization method. Setting the starting values right is crucial to achieving convergence and for having an efficient model. A lot of time can be invested here and Hess and Train (2017) suggest estimating an uncorrelated model first and to then use the received estimates as starting values for a model that allows for full covariance (cf. section 4.5 for the issue of correlation in MMNL). Alternatively, Bayesian estimations proved to be very effective, too (Hess and Train 2017). In our analysis however, the same starting values for all coefficients have been taken. Most of the times values of -0.1 generated the best results compared to values of 0, 0.1, 0.5 or 1. Regarding the random seed, it has been shown to be favourable to use quasi-random numbers generated by a Halton sequence instead of pseudo-random numbers (Bhat 2001 or Train 2009). Bhat (2001) found that 100 Halton draws are similarly accurate as 2000 pseudo-random draws. While on average the estimates remained similar, the standard deviations of the estimates were worse when comparing 1000 random draws to a 100 Halton draws in a study by Train (2009). A more recent study by Zeng (2016) confirms these findings and adds that even with an increasing number of observations, increasing the number of Halton draws does not necessarily improve estimators.

A first investigation for our data compares the Car/PT base model with 100, 250 and 500 Halton draws. The results are shown in Table 4. Increasing the number of draws from 100 to 250 raises the log-likelihood by about 7 points and decreases the Akaike Information Criterion (AIC) by 13 points. But another increase to 500 Halton draws worsens the metrics, even compared to the model with 100 draws. Hensher and Greene (2003) state the appropriate number of draws can vary enormously and increases with the number of random parameters and the correlation of attributes or alternatives.

They recommend estimating models over a range of 25 to 2'000 Halton draws. Restrictions in calculation power however limited the possibility to further investigate this issue within the scope of this thesis.

Table 4: Comparison of 100, 250 and 500 draws (Car/PT base model)

	100 Halton draws	250 Halton draws	500 Halton draws
No. of estimated parameters	59	59	59
Number of respondents	1955	1955	1955
Number of choice observations	7976	7976	7976
Number of draws	100	250	500
LL(null)	-5528.54	-5528.54	-5528.54
LL(final)	-3540.53	-3533.79	-3542.92
McFadden R2	0.36	0.36	0.36
AIC	7199.06	7185.57	7203.85
AICc	7202.79	7189.31	7207.58
BIC	7611.12	7597.64	7615.91

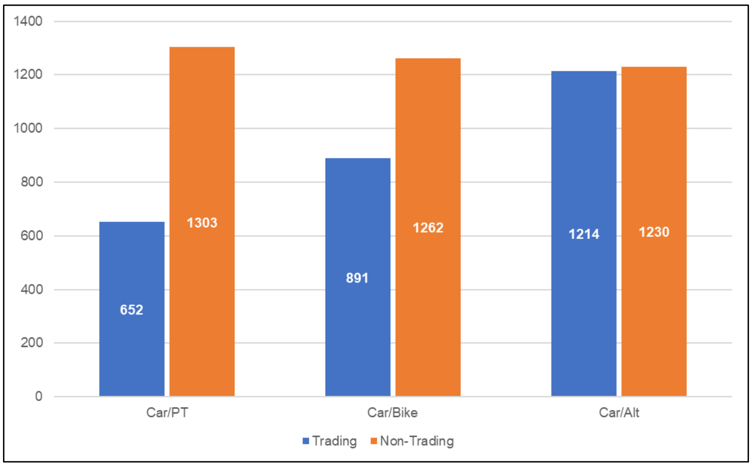
The “mixl” package provides the Halton sequence and for all models presented in this thesis, a 100 Halton draws have been set. Molloy et al. (2019) showed how estimation time and memory usage increases linearly with the number of draws in their “mixl” package. With a regular quad-core machine, an estimation with one thousand random draws can be done in less than 5 hours. However, the multicore-feature, which requires an additional setup for computers running Windows or macOS, caused some issues in our analysis, yet to be solved.

4.3. Descriptive analysis of choice behaviour

In 47.5% of all choice situations the respondent was willing to take the proposed alternative compared to their car trip. In Car/PT choice situations, the alternative PT was chosen in about one third of all cases (34.9%). In Car/Bike situations, the alternative option Bike was chosen 37,1% of times and Alt was chosen 60.8% of times in Car/Alt choice situations. One could expect the participants' experiences during the Smartphone tracking phase to influence choice behaviour but the distribution of choices according to the different experimental groups (pricing, nudging and control) of the MOBIS experiment does not change the picture.

Looking over all three choice sets, about 90% of all respondents switched at least once between alternatives over all choice sets. 10% choose the same alternative (i.e. alternative Car) in all twelve choice situations. Such behaviour is known as “non-trading” choice behaviour and indicates not enough trade-off variation between alternatives (Schmid et al. 2016). Figure 2 presents a closer look into the different choice situations.

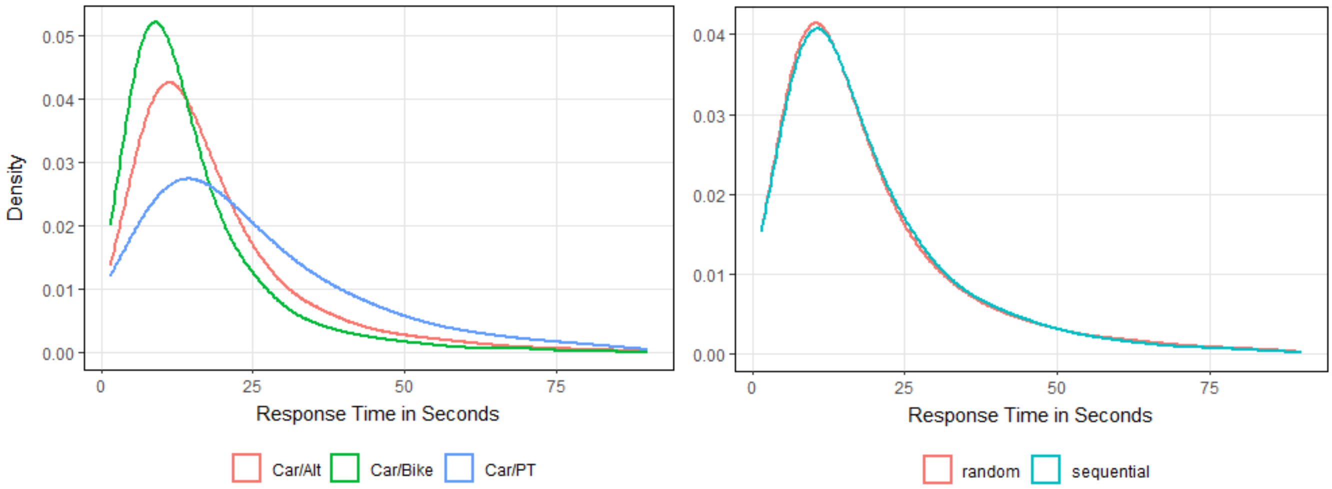
Figure 2: Trading and non-trading behaviour within choice types



In Car/PT situations, exactly one third of respondents switched their choices at least once. In Car/Bike situations it was 41.4% and in Car/Alt situations 49.7%. The limitation of this perspective is that not all participants received the same ratio (meaning 4xCar/PT, 4xCar/Bike and 4xCar/Alt) of choice situation types. Car/Alt is overrepresented so that trading was even higher relative to the number of choices for this situation.

As mentioned before, our dataset also contains the time it took respondents to make their decision. Alós-Ferrer et al. (2018) pointed to an important issue in modelling choices; the fact that the distributional assumptions necessary in random utility models influence the results. And the problem, that with the right assumptions, results can turn in one or the other direction. They show that by including people's response times to choices into random utility models, this issue can be reduced. The idea is, that the faster a respondent can take a decision, the bigger is their utility difference of two alternatives, so that the distribution of response times contains information about the (unobservable) distribution of utility. The proposal of Alós-Ferrer et al. (2018) is very appealing, as response times are observable, and its data is "cheap" to receive. Also, unobserved heterogeneity is taken care of, as it allows the utility difference to vary between individuals. Even though the MOBIS Study measured the response times of respondents in the SP experiment, the theoretical approach of Alós-Ferrer et al. (2018) did not fit our data well enough. The participants in our experiment responded all to their own individual journey, meaning they did not face the exact same decision. Nevertheless, it is possible to take some inferences from the distribution of response times in the experiment. In our data, the response time is defined as the total amount of time the respondent spent on the web page, that is the time until the respondent clicked the next button at the bottom of the page. It is therefore only an approximation on the real response time. There could have been an interruption not related to the online questionnaire until the respondent clicked next. For the analysis of response times, values below 1.5 seconds and above 90 seconds were excluded to get a more realistic picture. Figure 3 shows response time distributions depending on the choice situation type and the questionnaire mode.

Figure 3: Response time distributions per choice type and questionnaire mode



The median decision-maker had 19.4 seconds for a Car/PT decision, 11.5 seconds for a Car/Bike decision and 14.4 seconds for a Car/Alt decision. It is interesting enough to note that choosing between public transportation versus car took the median person about 2/3 longer than for a decision where the alternative was bike. According to the approach of Alós-Ferrer et al. (2018), this would mean that the utility difference between car and bike is much bigger than between car and PT. However, we should remember that the PT option had up to 17 lines of information, bike options 10 lines and the alternative journey time 11 lines of information which the decision maker had to process. If we take the number of information into account, the picture changes slightly, and Car/PT choices were even made a little bit faster than the other two. However, the experiment was conducted online, meaning under non-ideal conditions, and we do not know how thoroughly all the information was processed.

When designing the online questionnaire, two different presentation modes were implemented. If we compare whether the choice situations were sequential (i.e. all the same transportation modes in a row) or the choice situations came random, we cannot see any difference between the two questionnaire modes. Therefore, people having the same mode (car vs. bike for example) four times in a row did not benefit in terms of quicker decision-making than people with random order.

4.4. Choice model results

The focus in this thesis is on two model specifications. The base models include only alternative specific variables, meaning all variables listed in the choice situation as seen in Figure 1 or Annex 1. The cost coefficients are hereby broken down to their smallest entity. Compared to the base models, the full models include additional controls (Table 3). These give additional insights and the models, especially the cost coefficients, important for later willingness to pay calculations, got more realistic. This comes at the price of dropping some observations due to non-available values. Nevertheless, it seemed beneficial to work with these controls.

All cost variables are normalised for income. In earlier models without income normalisation some cost coefficients like car_priv_cost had positive signs in most specifications which were not regarded as realistic. Income, however, is not available as a continuous variable in the MOBIS data, so that five groups of income (see Table 3) had to be used. Equation (4.1) shows a simplified specification of the utility function for utility U_{car}, where β_j' is a vector of parameters for attribute j (tc = travel cost, aa = additional attributes) and X_j the value vector for attribute j. All cost parameters have been normalized for income with $\bar{x}_{inc}$ as the sample mean of income (in CHF/month) and λ_{inc} is an elasticity parameter.

$$U_{car} = \beta_{tc}^{'} * X_{tc} * \left(\frac{X_{inc}}{\bar{x}_{inc}}\right)^{\lambda_{inc}} + \beta_{aa}^{'} * X_{aa} + \varepsilon \qquad (4.1)$$

The utility function is specified the same for all the other three alternatives in the base model. In the full model however, the individual specific controls have been added to the utility of PT, Bike or Alt.

Tables 6, 8 and 10 show the results of the full model for the three choice-situation Car/PT, Car/Bike and Car/Alt. The coefficients of the variation have been suppressed for clarity purpose but are listed in Annex 2. Tables 5, 7 and 9 show the related metrics of the estimation and compare it to the base model (Annex 3).

The full choice model for Car/PT, contains a total of 95 estimated parameters (Table 5), where all, except for the (non-linear) income elasticity parameter, entered the model as random coefficients and were given a normal distribution, which allows them to take either sign. Compared to the base model, the full model increases the log-likelihood by 92 points and decreases the Akaike Information Criterion, AIC, by 112 points. If the number of observations divided by the free parameters falls below 40, it is recommended to use the AICc, which includes a correction for finite samples (Wagenmakers and Farrell 2004). In all our models, this ratio is between 84 and 198, so that the samples are sufficiently large to focus on the general AIC. The McFadden R^2 is a pseudo-R^2 analogous to the R^2 from linear regression models. It tries to capture the overall fit of the model based on the log-likelihood values. Its level, however, cannot directly be compared to the one of a linear regression model because of the non-linearity of the MNL model. Hensher et al. (2015, p. 456) state that “pseudo-R^2 values between the range of 0.3 and 0.4 can be translated as an R^2 of between 0.6 and 0.8 for the linear model equivalent”. In our case, the full model increases the pseudo-R^2 from 0.36 to 0.38.

Table 5: Model metrics - Car vs PT

	Base Model	Full Model
No. of estimated parameters	59	95
Number of respondents	1955	1955
Number of choice observations	7976	7976
Number of draws	100	100
LL(null)	-5528.54	-5528.54
LL(final)	-3540.53	-3448.32
McFadden R2	0.36	0.38
AIC	7199.06	7086.65
AICc	7202.79	7096.46
BIC	7611.12	7750.15

In the model output in Table 6, we see that for most cost and time coefficients, the signs are as expected, where higher costs or longer travel time adds negatively to utility. Car_ext_co2 gets out of line with a positive coefficient and significance at the 10% level. The time parameters are highly significant for both alternatives. For PT the private costs and for Car the congestion costs are highly significant as well. Car private costs increased in significance compared to the base model (see Annex 3) but remain out of the 10% significance level. Beside cost and time parameters, weather conditions are highly significant. Warm_wet and warm_dry add positively to PT’s utility compared to the reference category cold_dry. Unsurprisingly, owning a car highly increases the chance to choose the Car alternative, whereas owning a public transportation pass lets one increasingly choose PT.

An interesting insight is gained by the two variables congestion and emission; seeing congestion as an important issue increases the chance of choosing car, whereas seeing greenhouse gas emissions from motorized traffic as an important issue the picture is exactly the other way around. This gives a first indication how political convictions are related to the choice of transportation modes - with causalities remaining unclear, of course.

Table 6: Full model - Car vs PT

	Coefficient	Estimate	Robust S.E.	Pr(>|t|)
1	beta_car_priv_cost	-0.133	0.083	0.11
2	beta_pt_priv_cost	-0.571***	0.182	0
3	beta_car_ext_congest	-0.081**	0.034	0.02
4	beta_pt_ext_congest	-0.097	0.065	0.14
5	beta_car_ext_co2	0.155*	0.081	0.06
6	beta_pt_ext_co2	-1.134	0.736	0.12
7	beta_car_ext_health	0.039	0.056	0.49
8	beta_pt_ext_health	0.245	0.306	0.42
9	beta_car_dur	-0.167***	0.049	0
10	beta_pt_travel	-0.155***	0.038	0
11	beta_pt_access	-0.175***	0.058	0
12	beta_car_rel2	-0.627*	0.318	0.05
13	beta_car_rel3	-0.267	0.327	0.41
14	beta_car_rel4	-0.473	0.284	0.10
15	beta_pt_rel2	-0.208	0.258	0.42
16	beta_pt_rel3	0.094	0.295	0.75
17	beta_pt_rel4	0.342	0.276	0.21
18	beta_pt_weather2	0.566*	0.298	0.06
19	beta_pt_weather3	1.179***	0.331	0
20	beta_pt_weather4	1.063***	0.314	0
21	beta_pt_mode2	0.542	0.690	0.43
22	beta_pt_mode3	0.348	0.408	0.39
23	beta_pt_mode4	1.279	0.784	0.10
24	beta_pt_occ2	0.485*	0.272	0.07
25	beta_pt_occ3	0.395	0.260	0.13
26	beta_pt_freq2	0.055	0.232	0.81
27	beta_pt_freq3	0.473**	0.216	0.03
28	beta_pt_changes	-0.465**	0.208	0.03
29	beta_age_dummy	0.333	0.417	0.42
30	beta_female	0.132	0.333	0.69
31	beta_higher_edu	0.411	0.298	0.17
32	beta_own_car_dummy	-2.000**	0.812	0.01
33	beta_own_motorbike_dummy	-0.349	0.460	0.45
34	beta_own_bike_ebike_dummy	0.045	0.333	0.89
35	beta_has_pt_pass_halffare	0.765**	0.352	0.03
36	beta_has_pt_pass_regional	1.596**	0.731	0.03
37	beta_has_pt_pass_ga	1.369*	0.813	0.09
38	beta_congestion	-1.311**	0.485	0.01
39	beta_emissions	1.591**	0.568	0.01
40	beta_health	1.335**	0.578	0.02
41	beta_statement_ext_costs	0.219*	0.111	0.05
42	beta_factor_half	0.244	0.281	0.38
43	beta_factor_double	0.528*	0.300	0.08
44	beta_factor_quad	0.131	0.344	0.70
45	beta_factor_oct	0.335	0.479	0.49
46	beta_household_size	-0.002	0.141	0.99
47	cost_inc_elast	0.248	0.189	0.19
48	ASC_pt	-0.820	1.115	0.46

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

The next two tables (Table 7 and 8) show the metrics of Car/Bike and Car/Alt models. On the first glance, the overall model fit in terms of pseudo-R2 is not as good as for the Car/PT model. The full Car/Bike model improves the log-likelihood by 52 points and the AIC decreases by 33 points. The Bayesian information criterion (BIC) however increases by 218 points, as the BIC has a larger penalty term for the number of parameters.

Table 7: Model metrics - Car vs Bike

	Base Model	Full Model
No. of estimated parameters	41	77
Number of respondents	2153	2153
Number of choice observations	7738	7738
Number of draws	100	100
LL(null)	-5363.57	-5363.57
LL(final)	-3912.68	-3860.26
McFadden R2	0.27	0.28
AIC	7907.36	7874.52
AICc	7908.99	7880.31
BIC	8192.47	8409.97

Looking at the model estimates, we see that many of the additional variables that were added to the base model are insignificant. The model output suggests for example that owning any PT pass does not play a major role in the choice between Car or Bike. Neither does a higher education and surprisingly nor does age. The latter however could in a future model be broken down into more age categories for Car/Bike decisions, which could make it more meaningful. In contrast, owning a bike or e-bike increases the chance to choose the bike option and so does having a participant who sees greenhouse gas emissions or negative health effects of air pollution from motorized traffic as a major problem that should receive more attention from policy makers. Concerning the alternative specific variables, the weather dummies are all highly significant and show a utility increase compared to the reference level of cold_dry weather conditions. At least for the cold_wet condition (bike_weather2), the intuition would however expect negative utility. A future model could try to focus on either wet/dry or cold/warm weather dummies to make them easier to interpret. Bike lanes increased the choice of Bike compared to no bike lanes. Duration adds negative to utility of both alternatives.

Table 8: Full model - Car vs Bike

	Coefficient	Estimate	Robust S.E.	Pr(>|t|)
1	beta_car_priv_cost	-0.940	0.758	0.22
2	beta_car_ext_congest	-0.018	0.034	0.60
3	beta_car_ext_co2	0.104	0.139	0.46
4	beta_car_ext_health	0.276	1.157	0.81
5	beta_bike_priv_cost	-1.124	0.706	0.11
6	beta_bike_ext_health	0.298	1.064	0.78
7	beta_car_dur	-0.072**	0.032	0.03
8	beta_bike_dur	-0.303**	0.140	0.03
9	beta_car_rel2	0.320	0.225	0.15
10	beta_car_rel3	0.147	0.295	0.62
11	beta_car_rel4	0.147	0.222	0.51
12	beta_bike_weather2	1.849***	0.439	0
13	beta_bike_weather3	1.298***	0.366	0
14	beta_bike_weather4	3.744***	0.770	0
15	beta_bike_mode2	0.639	0.453	0.16
16	beta_bike_lane2	0.726**	0.291	0.01
17	beta_bike_lane3	0.735**	0.305	0.02
18	beta_bike_benefit2	0.702	1.213	0.56
19	beta_bike_benefit3	0.877	1.249	0.48
20	ASC_bike	-5.623**	2.059	0.01
21	beta_age_dummy	0.101	0.313	0.75
22	beta_female	-0.215	0.286	0.45
23	beta_higher_edu	-0.026	0.400	0.95
24	beta_own_car_dummy	-0.616	0.763	0.42
25	beta_own_motorbike_dummy	0.688	0.457	0.13
26	beta_own_bike_ebike_dummy	1.167**	0.545	0.03
27	beta_has_pt_pass_halffare	0.246	0.386	0.52
28	beta_has_pt_pass_regional	-0.074	0.608	0.90
29	beta_has_pt_pass_ga	0.618	0.610	0.31
30	beta_congestion	0.449	0.300	0.13
31	beta_emissions	1.203**	0.514	0.02
32	beta_health	0.833**	0.368	0.02
33	beta_statement_ext_costs	0.107	0.149	0.47
34	beta_factor_half	0.110	0.231	0.64
35	beta_factor_double	0.234	0.258	0.36
36	beta_factor_quad	0.098	0.442	0.82
37	beta_factor_oct	0.274	0.609	0.65
38	beta_household_size	0.467**	0.178	0.01
39	cost_inc_elast	-0.130	0.097	0.18

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

The model for Car/Alt choices contains only 28 parameters in the base model and 67 in the full model (Table 9). The low amount in the base model is mainly because some variables contain the same information for both alternatives, therefore not having any variation and they must be included as choice situation specific variable with alternative specific coefficient. This is the case for the private, the external CO2 and the health costs. The costs out of congestion differ between the options as the main purpose of the Alt option is a change in the departure time in order to flatten the peak travel hours.

The full model however includes the same set of additional controls again. This improves the models log-likelihood by 38 points but does not change much on the AIC. It rather increases the AIC by 2 points and the stricter BIC increases by 294 points. Many of the additional variables in the full model do not lead to a better model. Same as for the Car/Bike model, some dummies could be improved with another specification and others could even be left out to make the model more efficient.

Table 9: Model metrics - Car vs Alt

	Base Model	Full Model
No. of estimated parameters	28	67
Number of respondents	2444	2444
Number of choice observations	13288	13288
Number of draws	100	100
LL(null)	-9210.54	-9210.54
LL(final)	-6413.55	-6375.46
McFadden R2	0.30	0.31
AIC	12883.10	12884.91
AICc	12883.77	12888.75
BIC	13092.95	13387.05

Most cost coefficients in the Car/Alt model are significant and except for alt_ext_co2 they show the expected negative sign. Time departure shifts of +/- 30min increase utility of the Alt option compared to leaving 60min earlier. Not totally unexpected, people who state that congestion and health issues related to motorized traffic should gain more attention from policy makers take a positive utility out of choosing the Alt option.

Over all three models, the dummies capturing the multiplication of the external costs are with one exception not significant at the 10% level, so that we can assume a linear relationship. Also, in all three models, gender did not play any significant role and the same holds for being over 42 years old or having a tertiary education. The income elasticity for travel costs is insignificant at the 10% level in all three models. Normally one could expect decreasing utility with higher travel costs and that higher income respondents are less price sensitive. However, it could be, that our data on income and the grouping that had to be done is too imprecise.

Table 10: Full model - Car vs Alt

	Coefficient	Estimate	Robust S.E.	Pr(>|t|)
1	beta_car_ext_congest	-0.057***	0.020	0
2	beta_alt_ext_congest	-0.057*	0.031	0.06
3	beta_car_dur	-0.130***	0.014	0
4	beta_alt_dur	-0.096***	0.012	0
5	beta_car_rel2	0.054	0.111	0.63
6	beta_car_rel3	0.178	0.123	0.15
7	beta_car_rel4	0.658***	0.121	0
8	beta_alt_rel4	0.840***	0.111	0
9	beta_alt_time_dep2	1.651***	0.234	0
10	beta_alt_time_dep3	1.109***	0.245	0
11	beta_alt_time_dep4	-0.670***	0.178	0
12	beta_alt_priv_cost	-0.088**	0.037	0.02
13	beta_alt_ext_co2	0.102*	0.052	0.05
14	beta_alt_ext_health	-0.039	0.025	0.11
15	beta_age_dummy	-0.191	0.170	0.26
16	beta_female	-0.061	0.164	0.71
17	beta_higher_edu	-0.289	0.350	0.41
18	beta_own_car_dummy	-0.652	0.505	0.20
19	beta_own_motorbike_dummy	0.036	0.409	0.93
20	beta_own_bike_ebike_dummy	-0.380	0.250	0.13
21	beta_has_pt_pass_halffare	-0.258	0.179	0.15
22	beta_has_pt_pass_regional	0.099	0.231	0.67
23	beta_has_pt_pass_ga	-0.496*	0.279	0.08
24	beta_congestion	0.460**	0.189	0.01
25	beta_emissions	0.126	0.237	0.60
26	beta_health	0.601**	0.235	0.01
27	beta_statement_ext_costs	0.166	0.110	0.13
28	beta_factor_half	0.074	0.122	0.54
29	beta_factor_double	-0.170	0.131	0.19
30	beta_factor_quad	0.158	0.159	0.32
31	beta_factor_oct	0.176	0.248	0.48
32	beta_household_size	-0.052	0.069	0.44
33	cost_inc_elast	-0.090	0.871	0.92
34	ASC_alt	-0.223	0.578	0.70

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

4.5. Correlation in mixed MNL models

In contrast to a cross-sectional data set, panel data bears the risk of correlation between observations. Stated preference (SP) data with multiple choice situations per individual is such an example. If one allows variation in parameters across individuals to capture their heterogeneity, which is the essence of mixed logit models, there is the possibility of correlation between these individual parameters (Hensher and Greene 2003). If two parameters are correlated which each other, this simply means that the preference of a consumer for the first attribute is related to his preferences for the second attribute (Hess and Train 2017). In our SP data, it could for example be, that respondents who are cost sensitive react stronger on private as well as on external costs. Or it could be that people giving high value to the health benefit of a bike ride are less critical on the weather conditions during their trip.

A specific “type” of such correlation is called scale heterogeneity and describes the phenomenon that one person’s choice might differ by how much it is influenced by factors included in the model versus factors not included in the model, compared to another person. The results are different magnitudes of all the utility coefficients over the set of people. A person whose choice is mainly driven by unincluded factors will have utility coefficients that are smaller in magnitude than the ones of a person whose choice is strongly impacted by included factors, leading to correlation among the coefficients of the included variables (see for example Hensher et al. 2015 or Hess and Train 2017). In our data, some responders might be largely influenced by cost coefficients while others might be more influenced by convictions and habits that we have not captured. What makes it difficult is that correlation which is estimated between two coefficients cannot be distinguished empirically from its source. It could be scale heterogeneity taking place or any other complex pattern of positive and negative correlation between coefficients. Only general evaluations can be made, and Hensher et al. (2015) suggest estimating a whole set of different models in order to evaluate the potential role of preference heterogeneity and scale heterogeneity.

The “mixl” package allows for correlation between parameters and calculates a full covariance matrix for the post estimation. For our three (full) models, a first investigation rarely states correlations above 0.1 between any parameters. However, Hensher and Greene (2003) point out that for a model like ours, with several random parameters that are allowed to correlate, the standard deviations of the parameters are no longer independent. Using the Cholesky decomposition, they can be decomposed into the part that accounts for the related attribute and the part that captures the attribute-interaction. But such further investigation has not yet been done for our models.

4.6. Willingness-to-pay indicators

One of the most common willingness-to-pay (WTP) indicators is the value of travel-time savings (VTTS) measure. It can for example be used to calculate cost-benefit analysis when planning new transport systems or to implement efficient pricing systems. For linear-in-variables utility functions, it is simply calculated by dividing the travel-time (tt) coefficient by the travel-cost (tc) coefficient, β_{tt}/β_{tc}, which results in marginal utilities of an increase by one unit in travel-time and travel-cost (Hess et al. 2005). But not only values of travel-time savings, but any other WTP ratio can be calculated. However, these calculations are only as good as the underlying model and Hess et al. (2005) discuss biases from using the wrong distribution (cf. section 2.3). They suggest not to use normal or log-normal distributions but rather a Triangular or Johnson's S_B distribution and to estimate the bounds from the underlying data. Nevertheless our model has until now only used normal distributions for all variables. This could be one of the reasons why our VTTS estimates are somewhat different than those in other studies. A group of studies, mentioned in section 2.3, has investigated VTTS for Switzerland and other European countries and serves as comparison for our results.

A general formulation of the VTTS for respondent i looks as follows:

$$VTTS_i(inc) = \frac{\beta_{tt,i}*60}{\beta_{tc}*\left(\frac{X_{inc}}{\bar{x}_{inc}}\right)^{\lambda_{inc}}} \text{ CHF/h} \qquad (4.2)$$

Table 11 lists several VTTS calculations from the three different models, averaged at sample mean. Be aware that the column "Ratio" does not show the full calculation (which is done using formula 4.2) but is given to be precise on which variables were used. Whenever a coefficient was insignificant at the 10%-level or had the wrong expected sign it was not used for calculating a VTTS. Hence the number of VTTS that are meaningful is unfortunately limited. For the Car/PT model, five VTTS estimates were calculated. "VTTS Car" results in a value of 77.15 CHF/h or 12.85 CHF for 10 minutes. Intuitively, the assumption that the average participant of our experiment is willing to pay almost 13 CHF in order to save 10 minutes of travel time in a car seems rather high. Axhausen et al. (2008) found a VTTS of 31 CHF/h for car trips that had the purpose of commuting. For business trips however they found a value of about 50 CHF. Although one can expect the value of avoiding one hour of congestion to be higher than for regular driving, the 126.75 CHF/h based on the Car/PT model seem again rather high. However, our experiment has intentionally increased external costs above their usual which has not yet been considered.

The task for respondents was to consider the total costs of the trip. For Car/PT the car_ext_congest parameter is significant and we can include it in the calculation. The effect is a weighted average of both coefficients which results in a VTTS of 46 CHF/h. The estimated VTTS for PT are close to those in other studies. Schmid et al. 2016 reported around 20 CHF/h for PT in-vehicle time and Axhausen et al. (2008) 28 CHF/h for commuting and roughly 20 CHF for trips with the purpose of leisure or shopping. VTTS for PT access or egress time is somewhat higher than for in-vehicle time, which can be explained as this time can be less used to pursue other activities.

Table 11: Values of travel time savings (VTTS)

		Ratio	CHF/h
Car/PT Model			
	VTTS Car	$\frac{car\_dur}{car\_priv\_cost}$	77.15
	VTTS Congestion 1	$\frac{car\_dur}{car\_ext\_congest}$	126.75
	VTTS Car (avg.)	$\frac{car\_dur}{(car\_priv\_cost+car\_ext\_congest)}$	46.05
	VTTS PT in-vehicle	$\frac{pt\_travel}{pt\_priv\_cost}$	16.75
	VTTS PT access/egress	$\frac{pt\_access}{pt\_priv\_cost}$	18.90
Car/Bike Model			
	VTTS Bike	$\frac{bike\_dur}{bike\_priv\_cost}$	16.00
Car/Alt Model			
	VTTS Alt priv	$\frac{alt\_dur}{alt\_priv\_cost}$	65.30
	VTTS Alt (avg.)	$\frac{alt\_dur}{(alt\_priv\_cost+alt\_ext\_congest+alt\_ext\_health)}$	31.70
	VTTS Congestion 2	$\frac{alt\_dur}{alt\_ext\_congest}$	100.60
	VTTS Congestion 3	$\frac{car\_dur}{car\_ext\_congest}$	134.90

For the Car/Bike model it is hardly possible to calculate any WTP ratios. Most of the cost coefficients are insignificant and some have positive signs. It will need further improvements of the model to afford reliable conclusions. The duration estimates are significant though and calculating a VTTS using bike_priv_cost results in 16 CHF for saving one hour of cycling. Schmid et al. (2016) reported a much higher value of 60 CHF/h. Schmid et al. (2019) reported 12 Euro/h, although for Austria.

The Car/Alt model also faces the problem of lacking some robustness. However, we first find, that the “VTTS Alt priv” goes in the same direction than the value for car rides in the Car/PT model. Also, the VTTS’ for congestion are in a similar sphere as in the calculation from the Car/PT choice situations. Including external congestion and health costs, the VTTS for one hour of driving (given a shifted departure time) gets down to about 32 CHF and would be in line with Axhausen et al. (2008) who reported 31 CHF/h. For other meaningful WTP estimates the coefficients are either not significant or have the wrong expected sign. Results from the base model cannot help either.

Beside trying to further improve the robustness of the model in order to get better WTP estimates, a possibility can also be to directly estimate all taste parameters in the willingness to pay space by re-specifying the utility function. As in the study by Scarpa et al. (2008) described in section 2.3, Hensher et al. (2015 p.115) state two additional studies that found estimates in WTP space to produce much more reasonable results than when calculated by ratios of the parameters (Hensher and Greene 2011 and Train and Week 2005 cited in Hensher et al. 2015). However, it seems that the best method on how to get willingness to pay estimates strongly depends on the underlying data structure and the type of modelling used which in our case makes further efforts necessary.

5. Conclusion

5.1. Main findings, strengths and limitations

Using existing data from the MOBIS Research Project (2019), this study investigated choices for means of transportation in an SP experiment with a sample of more than 2'500 participants. Based on real car trips participants had conducted in the months before, alternative departure times were considered in about 61% of all situations, public transport in 35%, and the bike in 37%. Mixed MNL models were used for the estimation process and in addition to alternative specific attributes, a non-linear income elasticity term and socio-economic as well as other choice situation specific attributes were added, leading to comprehensive models.

What makes our study special is that instead of focusing solely on private costs, external costs were included as well, and participants were asked to consider them in their decisions. The estimated coefficients for external costs show the most significant effects for costs related to congestion whereas health and CO2 related costs play less of a role. One possible explanation is that people find it easier to connect to congestion costs as these are related to everyday experiences. As such, external costs did not play a major role even though the manipulation of these shifted the total costs even further into the direction of already less expensive PT and bike options. Much more of choice behaviour can be explained by convictions about transportation policies. People stating greenhouse gas emissions and health effects from motorized traffic as an issue that should receive more attention from policy makers attribute more utility to these options and vice versa for people seeing congestion as a major issue. VTTS calculations from the estimated models are in the expected range for the PT mode but show rather high values for car and bike modes reflecting the issue of not yet totally robust models.

Because the models are not yet optimal, results should be considered cautiously. Nevertheless, some preliminary suggestions for policy makers may be made. As time savings had a significant impact on the utility in all choices, it seems safe to suggest that more emphasis should be placed on the speed of public transport. On the other hand, knowledge of the external costs, such as CO2 emissions or congestion, only had an impact when the participant was privately convinced of their importance. A simple educational campaign on external costs generated by mobility choices is therefore unlikely to achieve many results. Rather, people's views would have to be addressed and changed - undoubtedly a much more difficult task. Another finding that is already being implemented in various communities is the importance of bike lanes, the existence of which led to an increase in decision-makers choosing the Bike alternative. Lastly, car ownership had a negative impact on participants' willingness to choose either PT or Bike. The question how car ownership might be reduced must be the subject of other studies, but the reduction of car ownership seems an important point for mobility policies.

This work started from scratch and initially a lot of time needed to be invested to get the modelling process started. The biggest limitation of the study therefor lies in the uncertainty regarding the model robustness and leads to some prospects for future research and improvements. As such, the study provides first insights from a methodological as well as content-related point of view and adds to our understanding on how to proceed further.

5.2. Future research

In general, more time needs to be invested into finding the "right" model. Mixed multinomial logit models offer a huge amount of possibilities and the approach highly differs from situation to situation. Hensher and Greene (2003 pp. 144-145) write:

> "It is important to allocate a good proportion of time estimating models in which many of the attributes of alternatives are considered as having random parameters. The possibility of different distributional assumptions […] for each attribute should also be investigated […]. The findings will not necessarily be independent of the number of random draws in the simulation […]. Establishing the appropriate set of random parameters requires consideration of the number (and type) of draws, the distributional assumptions and, in the case of multiple choice situations per individual, whether correlated choice situations are accounted for […]. These interdependencies may make for a lengthy estimation process."

Such effort could pay off by delivering more precise answers to our initial questions of transportation choice and its relation to social costs.

Our full models needed about 300 iterations until convergence. Hensher et al. (2015 p. 445) mention that too many iterations should make a researcher suspicious. The number of iterations depend however also on the complexity of the model as well as other settings. Nevertheless, the high number of iterations in our model should be motivation to try out further specifications and to work on making the model more efficient. Future models should be more specific on the choice situation. The Car/Bike choice situation may require a different specification than Car/PT situation and according to their distribution, some variables can be treated as fixed instead of random. The use of additional individual specific variables then (cf. table 3) should be weighed against having more observations. Another topic that could receive additional attention is potential correlation, which might bring insights on how to further improve the models. Due to the limited time of this thesis this was unfortunately not possible to evaluate further. Finally, the high proportion of "non-trading" for the PT and bike options suggest that future studies may want to consider more trade-off variation between alternatives.

The future of mobility may be deeply impacted by the covid-19 pandemic and future research may want to take these developments into account. A recent representative survey among

Swiss citizens indicated that the future of transportation could shift towards more individual traffic modes based on the experiences during the corona crisis (Deloitte 2020). As our data shows, individual investment decisions into transportation modes have long term consequences. Owning a car, PT pass or bike significantly increases the probability of choosing this option. Of course, it will need to be investigated from more distance, but covid-19 could change future traffic patterns and could just as well lead to a reduction in mobility. A follow-up study with participants of the MOBIS study on mobility behaviour during and after the recent corona lockdown is ongoing and promises interesting insights. It remains definitely important to understand the driving forces behind individual decisions for transportation modes to contribute to a more sustainable mobility system.

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Appendix

Appendix 1: Choice situation example for Bike and E-Bike

	Option 1: Velo	Option 2: Auto
Abfahrt	16:42	17:03
Ankunft	17:22	17:22
Dauer	40 min	19 min
Verspätung >10 min		Nie
Velostrecke	Hauptstrasse ohne Velostreifen	
Wetter	warm, nass	
Gesundheitsnutzen	hoch	
Gesamtpreis	1,40 CHF	10,75 CHF
privater Anteil	0,00 CHF	7,10 CHF
externer Anteil	1,40 CHF	3,65 CHF
→ Verursachter Stau		1,80 CHF
→ Gesundheits-/Unfallkosten	1,40 CHF	1,40 CHF
→ Klimaschäden		0,45 CHF
	Option 1 ○	Option 2 ○

	Option 1: E-Bike	Option 2: Auto
Abfahrt	16:52	17:03
Ankunft	17:22	17:22
Dauer	30 min	19 min
Verspätung >10 min		Nie
Velostrecke	Hauptstrasse ohne Velostreifen	
Wetter	kalt, nass	
Gesundheitsnutzen	hoch	
Gesamtpreis	7,75 CHF	21,80 CHF
privater Anteil	2,05 CHF	7,10 CHF
externer Anteil	5,70 CHF	14,70 CHF
→ Verursachter Stau		7,15 CHF
→ Gesundheits-/Unfallkosten	5,70 CHF	5,65 CHF
→ Klimaschäden		1,90 CHF
	Option 1 ○	Option 2 ○

Source: MOBIS Research Project (2019)

Appendix 2: Full model outputs (distr.) for PT, Bike and Alt

Table 12: Full model - Car vs PT - Sigmas

	Coefficient	Estimate	Robust S.E.	Pr(>|t|)
49	SIG_car_priv_cost	-0.079	0.049	0.110
50	SIG_pt_priv_cost	-0.456	0.166	0.010
51	SIG_car_ext_congest	-0.036	0.026	0.170
52	SIG_pt_ext_congest	0.047	0.041	0.250
53	SIG_car_ext_co2	-0.143	0.085	0.090
54	SIG_pt_ext_co2	1.514	0.525	0
55	SIG_car_ext_health	-0.273	0.089	0
56	SIG_pt_ext_health	-0.187	0.106	0.080
57	SIG_car_dur	0.085	0.016	0
58	SIG_pt_travel	-0.007	0.006	0.280
59	SIG_pt_access	-0.118	0.035	0
60	SIG_car_rel2	-1.655	0.622	0.010
61	SIG_car_rel3	0.654	0.467	0.160
62	SIG_car_rel4	-1.176	0.541	0.030
63	SIG_pt_rel2	-1.264	0.768	0.100
64	SIG_pt_rel3	-1.594	0.897	0.080
65	SIG_pt_rel4	-0.546	0.512	0.290
66	SIG_pt_weather2	-1.081	0.719	0.130
67	SIG_pt_weather3	-0.130	0.264	0.620
68	SIG_pt_weather4	-0.401	1.063	0.710
69	SIG_pt_mode2	-1.186	0.336	0
70	SIG_pt_mode3	-1.168	0.686	0.090
71	SIG_pt_mode4	-0.212	1.020	0.840
72	SIG_pt_occ2	-0.310	0.507	0.540
73	SIG_pt_occ3	-0.975	0.484	0.040
74	SIG_pt_freq2	-1.584	0.669	0.020
75	SIG_pt_freq3	1.114	0.539	0.040
76	SIG_pt_changes	-1.023	0.282	0
77	SIG_age_dummy	1.554	0.517	0
78	SIG_female	1.623	0.470	0
79	SIG_higher_edu	-0.086	0.471	0.850
80	SIG_own_car_dummy	-0.945	0.303	0
81	SIG_own_motorbike_dummy	-1.106	0.953	0.250
82	SIG_own_bike_ebike_dummy	0.880	0.233	0
83	SIG_has_pt_pass_halffare	-0.804	0.376	0.030
84	SIG_has_pt_pass_regional	-0.580	0.414	0.160
85	SIG_has_pt_pass_ga	-2.661	1.097	0.020
86	SIG_congestion	0.981	0.514	0.060
87	SIG_emissions	-0.304	0.446	0.500
88	SIG_health	-0.833	0.393	0.030
89	SIG_statement_ext_costs	-0.232	0.209	0.270
90	SIG_factor_half	0.582	0.282	0.040
91	SIG_factor_double	-0.101	0.257	0.690
92	SIG_factor_quad	0.234	0.450	0.600
93	SIG_factor_oct	-0.014	0.318	0.970
94	SIG_household_size	-0.232	0.073	0
95	SIG_pt	-3.127	0.793	0

Table 13: Full model - Car vs Bike - Sigmas

	Coefficient	Estimate	Robust S.E.	Pr(>|t|)
40	SIG_car_priv_cost	-0.352	0.089	0
41	SIG_car_ext_congest	0.101	0.037	0.010
42	SIG_car_ext_co2	-0.338	0.091	0
43	SIG_car_ext_health	-0.262	0.325	0.420
44	SIG_bike_priv_cost	-2.047	0.541	0
45	SIG_bike_ext_health	-0.267	0.064	0
46	SIG_car_dur	0.000	0.032	0.990
47	SIG_bike_dur	-0.015	0.020	0.460
48	SIG_car_rel2	-0.871	1.100	0.430
49	SIG_car_rel3	0.376	1.257	0.760
50	SIG_car_rel4	-1.173	0.725	0.110
51	SIG_bike_weather2	2.174	0.710	0
52	SIG_bike_weather3	-1.932	0.568	0
53	SIG_bike_weather4	-2.135	0.604	0
54	SIG_bike_mode2	0.514	0.393	0.190
55	SIG_bike_bike_lane2	-1.646	0.756	0.030
56	SIG_bike_bike_lane3	-0.547	0.603	0.360
57	SIG_bike_benefit2	-2.067	0.443	0
58	SIG_bike_benefit3	1.044	0.452	0.020
59	SIG_age_dummy	-2.471	0.648	0
60	SIG_female	0.774	0.350	0.030
61	SIG_higher_edu	-0.921	0.951	0.330
62	SIG_own_car_dummy	-1.863	0.356	0
63	SIG_own_motorbike_dummy	2.727	0.873	0
64	SIG_own_bike_ebike_dummy	-0.500	0.269	0.060
65	SIG_has_pt_pass_halffare	-0.408	0.518	0.430
66	SIG_has_pt_pass_regional	-0.207	0.924	0.820
67	SIG_has_pt_pass_ga	-2.490	0.842	0
68	SIG_congestion	-0.641	0.392	0.100
69	SIG_emissions	0.895	0.532	0.090
70	SIG_health	-1.115	0.622	0.070
71	SIG_statement_ext_costs	-0.342	0.176	0.050
72	SIG_factor_half	0.640	0.413	0.120
73	SIG_factor_double	-0.325	0.988	0.740
74	SIG_factor_quad	1.190	0.507	0.020
75	SIG_factor_oct	0.500	0.333	0.130
76	SIG_household_size	-0.317	0.246	0.200
77	SIG_bike	2.320	0.542	0

Table 14: Full model - Car vs Alt - Sigmas

	Coefficient	Estimate	Robust S.E.	Pr(>|t|)
35	SIG_car_ext_congest	-0.048	0.029	0.100
36	SIG_alt_ext_congest	-0.022	0.029	0.430
37	SIG_car_dur	-0.039	0.018	0.030
38	SIG_alt_dur	-0.066	0.009	0
39	SIG_car_rel2	-0.381	0.254	0.130
40	SIG_car_rel3	0.665	0.358	0.060
41	SIG_car_rel4	0.841	0.225	0
42	SIG_alt_rel4	-1.096	0.152	0
43	SIG_alt_time_dep2	-1.685	0.431	0
44	SIG_alt_time_dep3	-1.667	0.540	0
45	SIG_alt_time_dep4	-1.426	0.497	0
46	SIG_alt_priv_cost	-0.059	0.015	0
47	SIG_alt_ext_co2	-0.106	0.080	0.180
48	SIG_alt_ext_health	0.015	0.104	0.890
49	SIG_age_dummy	-1.877	0.333	0
50	SIG_female	-1.227	0.577	0.030
51	SIG_higher_edu	0.551	0.191	0
52	SIG_own_car_dummy	-0.622	0.562	0.270
53	SIG_own_motorbike_dummy	0.309	0.514	0.550
54	SIG_own_bike_ebike_dummy	-0.382	0.212	0.070
55	SIG_has_pt_pass_halffare	-0.786	0.303	0.010
56	SIG_has_pt_pass_regional	-0.469	0.835	0.570
57	SIG_has_pt_pass_ga	-2.096	0.338	0
58	SIG_congestion	0.259	0.730	0.720
59	SIG_emissions	-0.649	0.737	0.380
60	SIG_health	-0.382	0.503	0.450
61	SIG_statement_ext_costs	-0.263	0.114	0.020
62	SIG_factor_half	-0.207	0.337	0.540
63	SIG_factor_double	-0.712	0.354	0.040
64	SIG_factor_quad	-0.301	0.422	0.480
65	SIG_factor_oct	-0.541	0.632	0.390
66	SIG_household_size	-0.008	0.075	0.920
67	SIG_alt	-2.286	0.153	0

Appendix 3: Base model outputs for PT, Bike and Alt

Table 15: Base model - Car vs PT

	Coefficient	Estimate	Robust S.E.	Pr(>|t|)
1	beta_car_priv_cost	-0.104	0.093	0.260
2	beta_pt_priv_cost	-0.240	0.139	0.080
3	beta_car_ext_congest	-0.072	0.025	0
4	beta_pt_ext_congest	-0.122	0.129	0.340
5	beta_car_ext_co2	0.290	0.061	0
6	beta_pt_ext_co2	-2.079	1.584	0.190
7	beta_car_ext_health	0.058	0.123	0.640
8	beta_pt_ext_health	0.641	0.697	0.360
9	beta_car_dur	-0.148	0.049	0
10	beta_pt_travel	-0.158	0.030	0
11	beta_pt_access	-0.157	0.043	0
12	beta_car_rel2	-0.415	0.304	0.170
13	beta_car_rel3	-0.207	0.332	0.530
14	beta_car_rel4	-0.341	0.275	0.220
15	beta_pt_rel2	-0.116	0.236	0.620
16	beta_pt_rel3	0.018	0.263	0.950
17	beta_pt_rel4	0.036	0.253	0.890
18	beta_pt_weather2	0.384	0.226	0.090
19	beta_pt_weather3	1.044	0.260	0
20	beta_pt_weather4	0.796	0.234	0
21	beta_pt_mode2	-0.308	0.586	0.600
22	beta_pt_mode3	0.989	0.517	0.060
23	beta_pt_mode4	1.788	0.746	0.020
24	beta_pt_occ2	0.343	0.202	0.090
25	beta_pt_occ3	0.214	0.238	0.370
26	beta_pt_freq2	0.041	0.188	0.830
27	beta_pt_freq3	0.386	0.218	0.080
28	beta_pt_changes	-0.488	0.110	0
29	cost_inc_elast	0.048	0.141	0.730
30	ASC_pt	0.394	0.581	0.500

Table 16: Base model - Car vs PT - Sigmas

	Coefficient	Estimate	Robust S.E.	Pr(>|t|)
31	SIG_car_priv_cost	-0.167	0.065	0.010
32	SIG_pt_priv_cost	0.034	0.369	0.930
33	SIG_car_ext_congest	0.090	0.058	0.120
34	SIG_pt_ext_congest	-0.027	0.108	0.800
35	SIG_car_ext_co2	-0.410	0.124	0
36	SIG_pt_ext_co2	-0.381	0.297	0.200
37	SIG_car_ext_health	-0.218	0.160	0.170
38	SIG_pt_ext_health	-0.600	0.104	0
39	SIG_car_dur	-0.063	0.022	0
40	SIG_pt_travel	-0.044	0.010	0
41	SIG_pt_access	-0.110	0.036	0
42	SIG_car_rel2	-1.335	0.454	0
43	SIG_car_rel3	0.519	0.522	0.320
44	SIG_car_rel4	-1.345	0.334	0
45	SIG_pt_rel2	0.863	0.516	0.090
46	SIG_pt_rel3	-0.874	0.806	0.280
47	SIG_pt_rel4	0.630	0.385	0.100
48	SIG_pt_weather2	-0.271	0.303	0.370
49	SIG_pt_weather3	-0.428	0.294	0.150
50	SIG_pt_weather4	-1.686	0.857	0.050
51	SIG_pt_mode2	-0.663	0.401	0.100
52	SIG_pt_mode3	3.019	0.848	0
53	SIG_pt_mode4	-0.536	1.222	0.660
54	SIG_pt_occ2	0.284	0.289	0.330
55	SIG_pt_occ3	-0.102	0.745	0.890
56	SIG_pt_freq2	-0.617	0.428	0.150
57	SIG_pt_freq3	-1.356	0.364	0
58	SIG_pt_changes	-0.644	0.486	0.180
59	SIG_pt	-3.880	0.370	0

Table 17: Base model - Car vs Bike

	Coefficient	Estimate	Robust S.E.	Pr(>|t|)
1	beta_car_priv_cost	-0.428	0.960	0.660
2	beta_bike_priv_cost	-0.530	0.787	0.500
3	beta_car_ext_congest	-0.010	0.023	0.650
4	beta_car_ext_co2	0.090	0.044	0.040
5	beta_car_ext_health	0.150	0.179	0.400
6	beta_bike_ext_health	0.178	0.185	0.340
7	beta_car_dur	-0.058	0.022	0.010
8	beta_bike_dur	-0.183	0.167	0.270
9	beta_car_rel2	0.351	0.204	0.090
10	beta_car_rel3	0.125	0.212	0.560
11	beta_car_rel4	0.127	0.201	0.530
12	beta_bike_weather2	1.675	0.256	0
13	beta_bike_weather3	1.081	0.190	0
14	beta_bike_weather4	3.129	0.357	0
15	beta_bike_mode2	0.475	0.356	0.180
16	beta_bike_lane2	0.686	0.204	0
17	beta_bike_lane3	0.549	0.206	0.010
18	beta_bike_benefit2	-0.037	1.728	0.980
19	beta_bike_benefit3	-0.036	1.772	0.980
20	cost_inc_elast	-0.160	0.324	0.620
21	ASC_bike	-1.006	1.801	0.580
22	SIG_car_priv_cost	-0.183	0.056	0
23	SIG_bike_priv_cost	-0.869	0.313	0.010
24	SIG_car_ext_congest	-0.008	0.049	0.860
25	SIG_car_ext_co2	-0.157	0.066	0.020
26	SIG_car_ext_health	0.399	0.110	0
27	SIG_bike_ext_health	-0.040	0.088	0.650
28	SIG_car_dur	-0.028	0.016	0.080
29	SIG_bike_dur	-0.003	0.007	0.700
30	SIG_car_rel2	-0.605	0.468	0.200
31	SIG_car_rel3	0.035	0.348	0.920
32	SIG_car_rel4	-0.267	0.612	0.660
33	SIG_bike_weather2	0.552	1.377	0.690
34	SIG_bike_weather3	-1.240	0.391	0
35	SIG_bike_weather4	-1.979	0.563	0
36	SIG_bike_mode2	2.446	0.348	0
37	SIG_bike_bike_lane2	0.189	1.699	0.910
38	SIG_bike_bike_lane3	-1.144	0.733	0.120
39	SIG_bike_benefit2	-0.515	1.158	0.660
40	SIG_bike_benefit3	1.442	0.517	0.010
41	SIG_bike	-3.695	0.397	0

Table 18: Base model - Car vs Alt

	Coefficient	Estimate	Robust S.E.	Pr(>|t|)
1	beta_car_ext_congest	-0.038	0.023	0.100
2	beta_alt_ext_congest	-0.013	0.028	0.650
3	beta_car_dur	-0.103	0.014	0
4	beta_alt_dur	-0.080	0.012	0
5	beta_car_rel2	0.008	0.093	0.930
6	beta_car_rel3	0.128	0.105	0.220
7	beta_car_rel4	0.587	0.106	0
8	beta_alt_rel4	0.757	0.090	0
9	beta_alt_time_dep2	1.544	0.147	0
10	beta_alt_time_dep3	0.859	0.176	0
11	beta_alt_time_dep4	-0.792	0.182	0
12	cost_inc_elast	-1.183	0.664	0.080
13	beta_alt_priv_cost	-0.059	0.014	0
14	beta_alt_ext_co2	0.075	0.055	0.180
15	beta_alt_ext_health	-0.016	0.023	0.490
16	ASC_alt	-0.501	0.221	0.020
17	SIG_car_ext_congest	-0.056	0.014	0
18	SIG_alt_ext_congest	0.017	0.025	0.490
19	SIG_car_dur	-0.014	0.021	0.490
20	SIG_alt_dur	0.019	0.015	0.220
21	SIG_car_rel2	0.009	0.251	0.970
22	SIG_car_rel3	0.379	0.289	0.190
23	SIG_car_rel4	0.716	0.322	0.030
24	SIG_alt_rel4	-0.745	0.285	0.010
25	SIG_alt_time_dep2	-1.711	0.184	0
26	SIG_alt_time_dep3	1.088	0.466	0.020
27	SIG_alt_time_dep4	-2.039	0.378	0
28	SIG_alt	-3.240	0.152	0

Table 19: Base model - Car vs PT - Metrics

	Value
estimated parameters	59.00
Number of respondents	2336.00
Number of choice observations	9540.00
Number of draws	100.00
LL(null)	-6612.62
LL(final)	-4187.41
McFadden R2	0.37
AIC	8492.83
AICc	8495.94
BIC	8915.46

Table 20: Base model - Car vs Bike - Metrics

	Value
estimated parameters	41.00
Number of respondents	2592.00
Number of choice observations	9362.00
Number of draws	100.00
LL(null)	-6489.24
LL(final)	-4715.00
McFadden R2	0.27
AIC	9512.00
AICc	9513.35
BIC	9804.92

Table 21: Base model - Car vs Alt - Metrics

	Value
estimated parameters	28.00
Number of respondents	2929.00
Number of choice observations	15952.00
Number of draws	100.00
LL(null)	-11057.08
LL(final)	-7658.48
McFadden R2	0.31
AIC	15372.97
AICc	15373.53
BIC	15587.93

Appendix 4: Overview online appendix

<u>Folders and Content:</u>

MASTER_THESIS_LS_ONLINE_APPENDIX

DataPrep	: preparation script and original data sets
FirstWave_mixl	: preliminary analysis using mixl-package
Mlogit_Analysis	: analysis using mlogit-package (incl. dataPrep into long-format)
Output	: all model outputs mentioned in this thesis
Tables and Figures	: all tables and figures provided in this thesis
TOP LEVEL FILES	: main scripts used in this thesis, on which output is based

Plagiatserklärung

„Ich bezeuge mit meiner Unterschrift, dass meine Angaben über die bei der Abfassung meiner Arbeit benützten Hilfsmittel sowie über die mir zuteil gewordene Hilfe in jeder Hinsicht der Wahrheit entsprechen und vollständig sind. Ich habe das Merkblatt zu Plagiat und Betrug vom 22.02.11 gelesen und bin mir der Konsequenzen eines solchen Handelns bewusst.“

Name, Vorname: Seiler, Leonard

Ort und Datum: Bern, 26.06.20

Unterschrift: